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Evaluation of uncertainty in capturing the spatial variability and magnitudes of extreme hydrological events for the uMngeni catchment, South Africa

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ABSTRACT

Downscaled General Circulation Models (GCMs) output are used to forecast climate change and provide information used as input for hydrological modelling. Given that our understanding of climate change points towards an increasing frequency, timing and intensity of extreme hydrological events, there is therefore the need to assess the ability of downscaled GCMs to capture these extreme hydrological events. Extreme hydrological events play a significant role in regulating the structure and function of rivers and associated ecosystems. In this study, the Indicators of Hydrologic Alteration (IHA) method was adapted to assess the ability of simulated streamflow (using downscaled GCMs (dGCMs)) in capturing extreme river dynamics (high and low flows), as compared to streamflow simulated using historical climate data from 1960 to 2000. The ACRU hydrological model was used for simulating streamflow for the 13 water management units of the uMngeni Catchment, South Africa. Statistically downscaled climate models obtained from the Climate System Analysis Group at the University of Cape Town were used as input for the ACRU Model. Results indicated that, high flows and extreme high flows (one in ten year high flows/large flood events) were poorly represented both in terms of timing, frequency and magnitude. Simulated streamflow using dGCMs data also captures more low flows and extreme low flows (one in ten year lowest flows) than that captured in streamflow simulated using historical climate data. The overall conclusion was that although dGCMs output can reasonably be used to simulate overall streamflow, it performs poorly when simulating extreme high and low flows. Streamflow simulation from dGCMs must thus be used with caution in hydrological applications, particularly for design hydrology, as extreme high and low flows are still poorly represented. This, arguably calls for the further improvement of downscaling techniques in order to generate climate data more relevant and useful for hydrological applications such as in design hydrology. Nevertheless, the availability of downscaled climatic output provide the potential of exploring climate model uncertainties in different hydro climatic regions at local scales where forcing data is often less accessible but more accurate at finer spatial scales and with adequate spatial detail.

1. Introduction

Several studies from southern Africa have shown that extreme hydrological events are increasing in frequency and magnitude (e.g., Kabat et al., 2002; Reason and Keibel, 2004; Kadomura, 2005; Patt and Schröter, 2008; Yanda, 2010; Goodess, 2013). For example, the El Niño-Southern Oscillation effect has continued to strengthen in recent decades: 1990–2000/2000–2010 (Timmermann et al., 1999; Manatsa et al., 2011) resulting in more floods and droughts. Several scholars believe that the El Niño-Southern Oscillations are becoming more intense as a result of climate change (e.g., McMichael et al., 2006; Collins et al., 2010; Manatsa and Behera, 2013). For example, in southern Africa, the frequency of droughts is projected to increase and will most likely increase the frequency of extreme low flows and low storage episodes (Desanker and Magadza, 2001). These will inevitably affect aquatic ecosystems, water supply, irrigation, leisure, and hydro power generation.

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On the other hand, Kusangaya et al. (2014) reported that some areas in southern Africa have, and will, experience an increase in the frequency and magnitude of heavy precipitation events which in most cases will result in flooding (and extreme high flows). To date, examples include recurring floods as reported by Artur and Hilhorst (2012). Overall, given the potential negative effects of extreme hydrological events, understanding is thus required as to whether, and to what extent, these extreme hydrological events (floods and droughts) and the subsequent river dynamics (high and low flows) are currently being captured when using General Circulation Models (GCMs) for climate projections. Insights generated from such studies are not only important in increasing confidence in the use of the GCMs output for impacts assessment but also in using results generated from such output for assessing potential climate change impacts in future.

GCMs are computer models which mathematically represent various physical processes of the Earth's system, and in which physical and biogeochemical processes are described numerically to simulate the climate system as realistically as possible (Wilby et al., 1999; Hulme et al., 2001; Randall et al., 2007). Although the physical processes are generally well known they are usually not fully represented in climate models owing to limitations in computing resources, inadequate input data and limited understanding of processes (Schulze, 2000a; Thornton et al., 2009; Tadross et al., 2011; Ganguly et al., 2014). Nevertheless, GCMs also provide climate output critical in driving hydrological models. To date, the availability of downscaled GCMs (dGCMs) output covering watersheds at finer spatial scales provides data for input into hydrological models for climate change impacts assessments.

Whilst downscaling produces climate information at scales finer than the initial projections, it uses additional information, data, and assumptions, which lead to further uncertainties and limitations (see: Jones et al., 2011; Chen et al., 2012; Nikulin et al., 2012; Wilby and Dawson, 2013; Dosio et al., 2014). Owing to these limitations, GCMs are considered to be the largest source of uncertainty in quantifying climate change impacts (Hewitson and Tadross, 2010; Thornton et al., 2010). Consequently, as reported elsewhere, downscaled GCMs output have often failed to capture the spatial variability and magnitudes of extreme hydrological events (Nemeth, 2010; Prudhomme et al., 2010; Willems et al., 2012; Ntegeka et al., 2014) and hence fail to capture the subsequent river dynamics (high and low flows). This is so despite the fact that high and low flows play a significant role in regulating the structure and function of rivers and associated ecosystems (Field, 2012).

Given that our understanding of climate change points towards an increasing frequency, timing and intensity of extreme hydrological events (e.g., Easterling et al., 2000; Groisman et al., 2005; Osbahr et al., 2008; Yanda, 2010; Yamba et al., 2011; Goodess, 2013), there is therefore the need to assess the ability of downscaled GCMs to capture these extreme hydrological events for southern Africa, in both urban and rural areas. On one hand, both urban and rural areas contain many types of hydraulic engineering structures (such as dams, levees, water distribution networks, water collection networks, sewage collection networks, storm water management, etc.) which need to be designed to accommodate peak flows of a certain magnitude in order to function safely at a given level of risk (Schulze et al., 2014). Should the structures fail, especially where human settlement is dense, there are potential economic environmental and societal consequences (Schulze et al., 2014). It is thus hypothesised that climate change, could result in changes in the intensity and frequency of extreme rainfall events. The emerging question is thus: How is the simulated streamflow (simulated using downscaled GCM climate output) capturing the spatial variability and magnitudes of extreme hydrological events (and the subsequent river dynamics: high and low flows) for the historical climate (1960–2000), for these GCMs to be used with confidence in future climate projections. The uMngeni Catchment in South Africa is used as a case study. The ACRU hydrological model was used in simulating streamflows.

2. Materials and methods

2.1. Study area

The uMngeni Catchment (4349 km^2), subdivided into 13 Water Management Units (WMUs) and is located in the KwaZulu-Natal Province of South Africa (Fig. 1). The mean annual precipitation (MAP) of the catchment varies from 1550 mm per annum in the main water source areas in the west of the catchment to 700 mm per annum in the drier middle reaches of the catchment (Summerton and Schulze, 2009; Summerton et al., 2009). The catchment is, however, characterised by high intra- and inter-annual rainfall variability. Mean annual temperature ranges from 12 °C in the escarpment areas to 20 °C towards the coastal areas of the catchment (Summerton et al., 2009). Fig. 1 shows the location of uMngeni Catchment in South Africa and the Acocks 1988 land cover types. The Acocks (1988) Veld Types baseline landcover were used in simulating streamflows for both the historical and dGCM based streamflow simulations that would occur under natural landcover. As stated in Kusangaya et al. (2017) the Acocks Veld Type maps are the most scientifically respected and generally accepted maps of natural vegetation for South Africa. Estimates of streamflow responses from the Acocks Veld Types have formed the basis for which streamflow reductions owing to land use change as outlined in the South African National Water Act (NWA, 1998) are assessed since 1998 (Gush et al., 2002) and, more recently, streamflow changes owing to climatic changes (Warburton et al., 2012).

The uMngeni Catchment supplies water to nearly 15% of SA's population, including the two largest cities: Pietermaritzburg with ±220 000 people and Durban with ±600 000 people (Stats-SA, 2012). Thus the catchment is home to a significant population who are potentially vulnerable to climate change especially given the projected increase in the occurrence of extreme hydrological events. Within the uMngeni catchment, there are four major dams (Alberts Falls, Midmar, Nagle and Inanda) which are used for water supply and leisure (boating and fishing) activities (Fig. 1). These activities are highly dependent on water availability and are likely to be affected by climate change.

The catchment is regarded as water stressed and regularly experiences droughts (Alexander, 1985; Diab and Scott, 1989; Alexander, 2001; Summerton, 2008; Summerton et al., 2010) as observed during the 2015–2016 rainfall season (uMngeni-Water, 2016). For example, the 2015–2016 season has been regarded as the worst drought season since 1904, with the KwaZulu Natal Province being one of the hardest hit provinces in South Africa (SAWS, 2017). Losses resulting from this drought have been estimated at over R400 million (Agri-SA, 2016). The impacts were particularly felt by the farming community which comprises of both commercial and subsistence farmers, with almost 10 000 provincial farmers affected, leaving around 40 000 heads of cattle dead, and severe crop losses (Agri-SA, 2016). Some of the major dams' storage capacity as of May 2016 were well below 50%, with Midmar Dam at 45.72% and Albert Falls Dam at 32.9% (uMngeni-Water, 2016). As a result, Umgeni Water has reduced the production of potable water. Water rationing and restrictions were implemented and this is likely to affect people's livelihoods (uMngeni-Water, 2016).

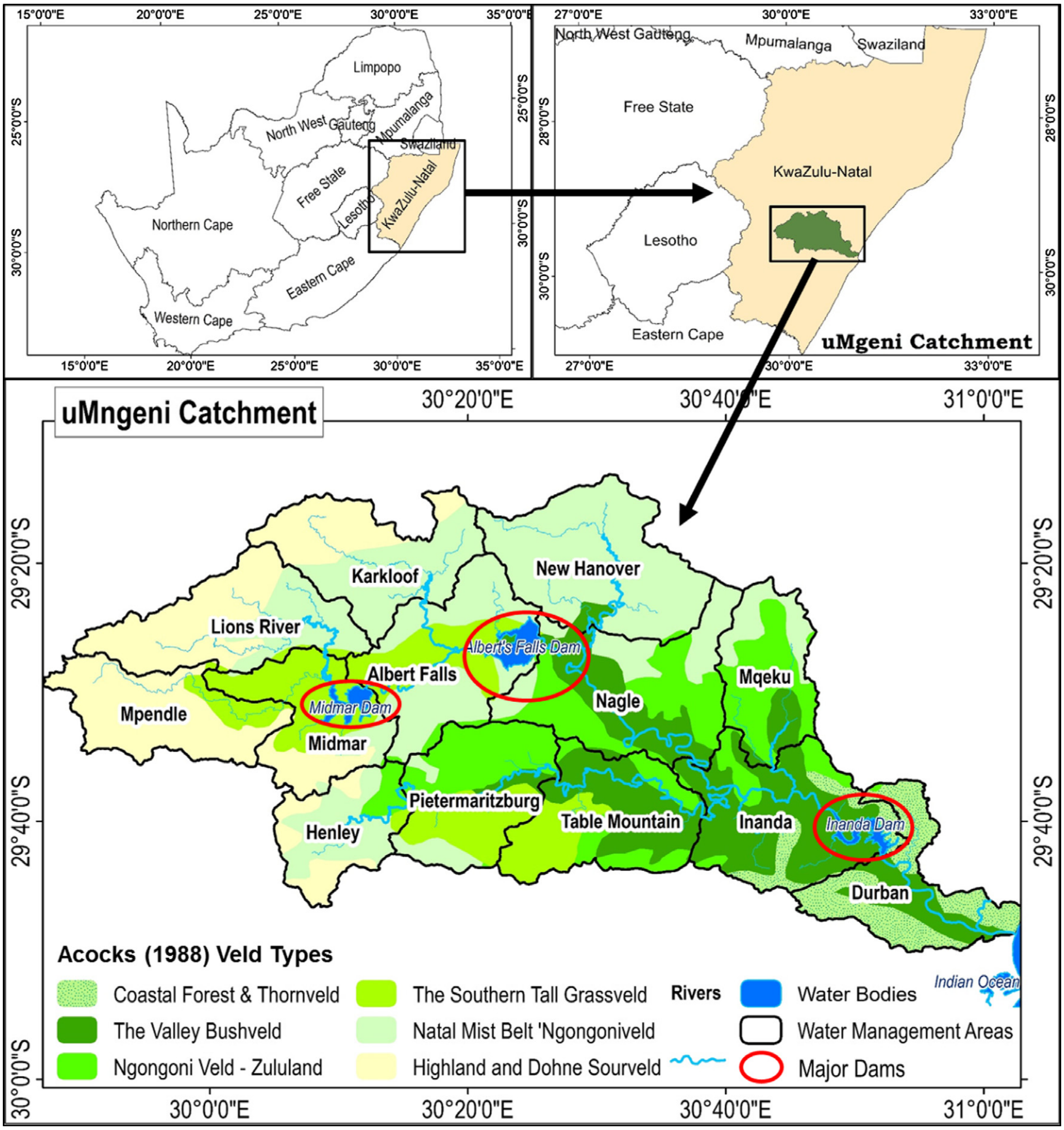

Fig. 1. The uMngeni Catchment in KwaZulu Natal Province, South Africa showing the Acocks (1988) baseline land cover within the 13 water management units as well as the location of some of the major dams (Midmar, Albert Falls & Inanda Dams) within the catchment.

Given the population at risk of these extreme hydrological events and financial losses incurred thereof, it is important that we understand the frequency of occurrence and impacts of these events in the uMngeni catchment. However, this requires an understanding of the uncertainties associated with the downscaled output in the first place.

Previous studies considering climate change impacts on hydrology in the uMngeni catchment (see, e.g., Tarboton et al., 1992; Summerton, 2008; Summerton et al., 2009; Summerton et al., 2010; Warburton et al., 2012) did not consider the uncertainty of downscaled products in capturing extreme high and low flows. Yet the understanding of these uncertainties is important in improving characterisation of climate related hydrological impacts in the catchment. Understanding how downscaled climate output captures extreme hydrological events and extreme river dynamics increases our confidence in the use of downscaled climate products for future hydrological projections as well as climate change impact studies.

2.2. Downscaled climate model output

The downscaled climate output were obtained from the Climate System Analysis Group at the University of Cape Town (CSAG – UCT). The climate data were statistically downscaled from the fifth phase of the Coupled Model Inter-comparison Project (CMIP5) at CSAG – UCT using the Self Organizing Map Downscaling (SOMD) method of Hewitson and Crane (2006). In a previous study, Kusangaya et al. (2016) observed that out of the ten downscaled GCMs used, only MIUB_ECHO_G (e11), GFDL_CM2_0 (g11), MRI_CGCM2_3_2A (mr1), CSIRO_MK3_5 (cs1) and MPI_ECHAM5 (e12) simulated historical rainfall (1960–2000) satisfactorily with cumulative rainfall found to be within ±10% of historical rainfall in the majority (7/13) of Water Management Units of the uMngeni Catchment. Additionally, evaluation of the intra-GCM variability showed that these five dGCM showed limited variability for mean rainfall as all dGCMs inter-quartile ranges were between ±15%. Based on these findings, climate output from the five dGCMs were

considered acceptable (±10% of rainfall mean and ±15% of rainfall variability) to used as input to the ACRU hydrological model in simulating streamflow. Table 1 provides the details of the five selected dGCMs.

2.3. Hydrological modelling

Downscaled GCMs do not simulate streamflow, thus projected hydrological time series were obtained through inputting dGCM climate data to drive a rainfall-runoff model and obtain projected streamflow responses. The ACRU hydrological model was used to simulate streamflow for the period 1961–2000 under a baseline land cover of Acocks (1988) Veld Types. The ACRU model (Schulze, 1995) is a physical-conceptual, daily time-step, multi-level, multi-purpose model that is conceptualized to adequately represent hydrological processes, and has also been shown to adequately represent catchment responses under different climate scenarios. The ACRU Model has been applied extensively in both land use and climate change impact studies in different hydro-climatological regions of southern Africa, as well as in modelling high and low flows (e.g., Tarboton et al., 1992; Schulze and Perks, 2000; Schulze, 2000b; Schulze et al., 2003; Schulze, 2005; Graham et al., 2011; Schulze, 2011; Kienzle et al., 2012). Warburton et al. (2010) showed that the ACRU Model can be used successfully for climate change impact studies in catchments with diverse land uses and climate regions. This increases the confidence that the ACRU Model provides a suitable and accurate representation of historical streamflow and reduces the uncertainty regarding the model's ability to simulate adequately different climate scenarios as obtained from the different dGCMs (Warburton et al., 2012).

The ACRU hydrological model is designed to simulate daily soil water budgets from which monthly and annual values can then be derived (Smithers and Schulze, 1995; Smithers et al., 1997; Schulze and Perks, 2000). The generation of streamflow in ACRU is based on the premise that, after initial abstractions (interception, depression storage and infiltration), streamflow produced is a function of the magnitude of the rainfall and the soil water deficit from a critical response depth of the soil (Schulze, 1995). The ACRU hydrological model is not a model in which parameters are calibrated to produce a good fit; rather values of input variables are estimated from the physical characteristics of the catchment (Smithers and Schulze, 1995) using available information. Details of ACRU configuration used in this study can be obtained from Warburton et al. (2010). The ACRU Model is explained in detail by Schulze (1995) and Smithers and Schulze (1995). Fig. 2 illustrates the conceptualization of the water budget in the *ACRU* model.

Parameter input values (soils, catchment characteristics, topography, etc.) as used by Warburton et al. (2010) in the configuration of the ACRU model were adopted for this study. The uMngeni catchment was delineated into 13 WMUs, which were further subdivided into 145 sub-catchments with respect to altitude, topography, soil properties and land cover as well as the river sub-catchment drainage system. The sub catchments were configured to cascade downstream in a logical sequence representative of river flow (Fig. 3). Cumulative streamflows from the outlets of five water management areas were selected for analysis of hydrological alteration, namely Midmar and Karkloof in the upper reaches of the catchment; Table Mountain and Nagle in the middle reaches of the catchment, and Durban at the lower catchment outlet (Fig. 3).

For the simulation of historical streamflow, daily rainfall data required as input to the ACRU model were extracted from a daily rainfall database for South Africa compiled by Lynch (2004) for the historical time period: 1960–2000. Daily temperatures were also extracted from a gridded database of daily temperatures for South Africa compiled by Schulze and Maharaj (2004) for the same time period: 1960–2000. On the other hand, for the simulation of GCM streamflow, statistically downscaled GCM rainfall and temperature data obtained from CSAG were used to as input for the ACRU hydrological model for the different downscaled climate models from 1960 to 2000.

The Acocks (1988) Veld Types baseline land cover were used in simulating streamflows for both the historical and dGCM based streamflow simulations that would occur under natural land cover. As stated in Kusangaya et al. (2017) the Acocks Veld Type maps are the most scientifically respected and generally accepted maps of natural vegetation for South Africa. Assessment of extreme hydrological events was carried out on cumulative streamflow data at the catchment outlet (streamflow in ACRU) based on the assumption that any variation of streamflow at the catchment outlet is representative of variation accumulated from the whole catchment i.e. it is the integrated flow at a point of the entire upstream area. Streamflows thus carry the 'memory', or 'footprint', of all rainfall-runoff processes (dependent on the climatic regime, soils, slope and land cover) which occurred upstream.

2.4. Assessment of hydrological variability

For this study, the Indicators of Hydrologic Alteration (IHA) method (Richter et al., 1996; Richter and Thomas, 2007) of the US Nature Conservancy (http://www.nature.org/) was adapted to

Table 1
Downscaled climate models obtained from CSAG – UCT (statistically downscaled from the fifth phase of the Coupled Model Inter-comparison Project) and used in this study to compare against historical rainfall and also to simulate streamflow.

GCM name	Country of origin	Host organisation	Acronym (*for this study*)	Climate data downscaled	Period
MIUB_ECHO_G	Germany and Korea	Meteorological Institute of the University of Bonn (MIUB, Germany) and Institute of KMA (Korea) and Model and Data group	e11	rainfall max. temp. min. temp.	1961–2000
MPI_ECHAM5	Germany	Max Planck Institute for Meteorology (MPI)	e12	rainfall max. temp. min. temp.	1961–2000
CSIRO_MK3_5	Australia	Commonwealth Scientific and Industrial Research Organisation (CSIRO)	cs1	rainfall max. temp. min. temp.	1961–2000
GFDL_CM2_0	USA	Geophysical Fluid Dynamics Laboratory, NOAA (GFDL)	g11	rainfall max. temp. min. temp.	1961–2000
MRI_CGCM2_3_2A	Japan	Meteorological Research Institute, Japan Meteorological Agency (MRI)	mr1	rainfall max. temp. min. temp.	1961–2000

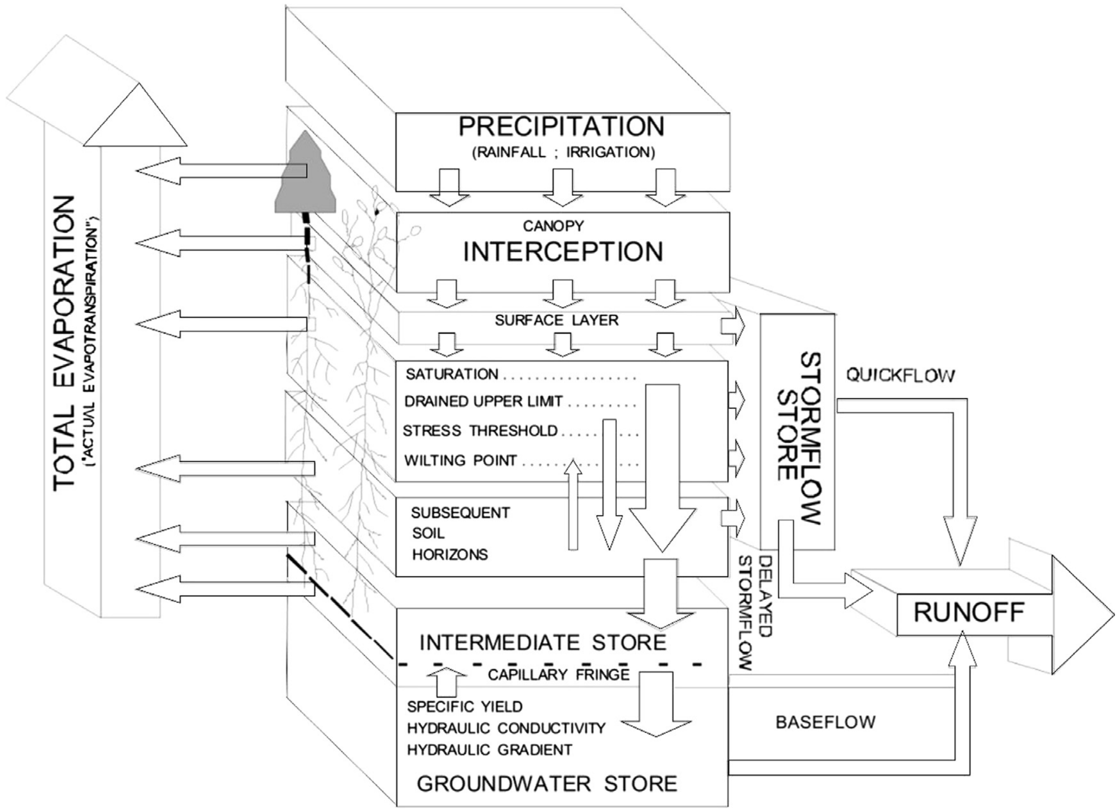

Fig. 2. Conceptual representation of the water budget in the ACRU model (Schulze, 1995; Schulze and Smithers, 2004).

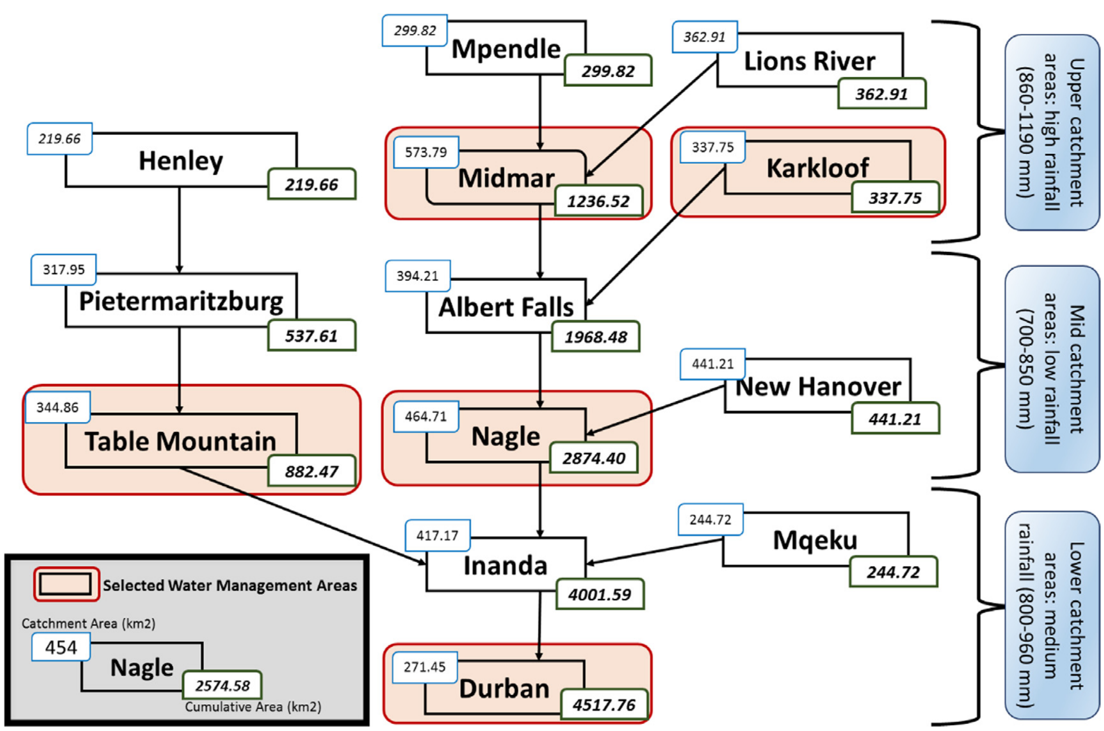

Fig. 3. The uMngeni catchment distributed hydrological modelling configuration for ACRU modelling and the five selected WMUs used in analysis of hydrological alteration.

assess how streamflow simulated using downscaled climate output adequately captures and approximates streamflow simulated using historical climate data. The IHA method gives a comprehensive list of indices which are widely and effectively used to analyse both high and low flows. Previous studies have successfully applied the methodology of IHA to assess impacts of anthropogenic drivers such as dam construction on streamflow (e.g., Taylor et al., 2003; Mathews and Richter, 2007; Yang et al., 2008; Zhang and

Döll, 2008; Zhang et al., 2009; De Winnaar and Jewitt, 2010; Kim et al., 2011; Saraiva Okello et al., 2015). Furthermore, Olden and Poff (2003) evaluated patterns of statistical variation among 171 published hydrological indicators and concluded that the 33 IHA indices capture the majority of the variation, and thus can be used to represent the major aspects of the flow regimes. Recently, Wobus et al. (2015) also effectively adapted the IHA methodology to characterize changes in the hydrology under a range of future climate scenarios. IHA can thus be considered to be a robust methodology, as it can indicate the degree of uncertainty in capturing extreme hydrological events between streamflow simulated using dGCM output and streamflow simulated using historical climate data. The data record length for analysis was from 1961 to 2000.

The IHA approach compares hydrological data sets by calculating multi-variate statistics to assess the degree of hydrological alteration, therefore enabling the characterization of river and catchment conditions (Puckridge et al., 1998; Clausen and Biggs, 2000; Pettit et al., 2001), and responses of the catchments to climate forcing (Wobus et al., 2015). This multi-variable approach allows the investigation of the multi-impacts of hydrological changes on the river channel and associated ecosystems (Mathews and Richter, 2007). The IHA software calculates a total of 67 parameters, subdivided into two groups – 33 hydrologic alteration (HA) parameters and 34 environmental flow component (EFC) parameters (Richter et al., 1996). For this study, 26 of the 33 HA (Group 1, 2, and 4) and 20 of the 34 EFC were adapted for assessing hydrologic alterations in terms of streamflow magnitude, frequency, duration and rate of change as well as performing a range of variability analysis (Table 2). These chosen indices are deemed cable of completely characterising hydrological characteristics of both high and low flows.

The flows exceeding the 75% (Q75) of the daily flows for the 40 year period were classified as high flows. Flows that were below the 25% (Q25) of the daily flows for the 40 year period were classified as low flows. A small flood event was defined as an initial high flow with a peak flow greater than that of the 2 year return interval event, whilst a large flood event was taken as an initial high flow with peak flow greater than that of the 10 year return interval event. An extreme low flow was defined as an initial low flow below 10% of daily flows for the period. Frequency refers to how often a flow above a given magnitude recurs over some specified time interval. Duration is the period of time associated with a specific flow condition. Peak flow denotes the maximum flow during an event and timing refers to Julian date of the flow (Nature-Conservancy, 2009). Non-parametric (median and percentile) statistics were used because of the skewed (non-normal) nature of hydrological datasets. HA parameters are calculated and organized in the output tables by water year from October 1 to September 30.

The Hydrologic Alteration factor for each of the parameters was calculated as outline by (Richter et al., 1996; Richter et al., 1998; Mathews and Richter, 2007) as follows:

1. For each parameter, IHA divides the full range of 'pre-impact data' (i.e. simulations from historical data) into three different categories, generally percentiles (e.g., lowest third, middle third, and highest third).
2. The 'post-impact' data (i.e. simulations from dGCM output) is then analysed and the observed distribution of data with the distribution expected from the pre-impact data compared.
3. Hydrologic Alteration (HA) factor was calculated as: = (observed frequency − expected frequency)/expected frequency.
4. A positive HA factor means that the frequency of values in the category (percentile grouping) had increased in the post-impact period, while a negative HA factor means that the frequency of values in the category (percentile grouping) had decreased in the post-impact period.

The maximum HA value is infinity, with a minimum value of −1. A positive HA value implies that the frequency of values in the category (high, medium and low RVA) has increased from the streamflow simulated using the historical climate data (pre-impact) to the streamflow simulated using the dGCM output (post impact). A negative value shows that the frequency of values in the category is lower for the streamflow simulated using the historical climate data as compared to streamflow simulated using the dGCM output (see Richter et al., 1997; Richter et al., 1998; Mathews and Richter, 2007).

2.4.1. Range of Variability analysis

The Range of Variability Approach (RVA) described in Richter et al. (1997) was implemented within the IHA for analysing the change between flows simulated using historical rainfall vs

Table 2
Summary of Indicators of Hydrologic Alteration (IHA) and environmental flow conditions (EFC) hydrological parameters used in analysing extreme river dynamics (high and low flows).

IHA Group 1: Magnitude of monthly water conditions	IHA Group 2: Magnitude and duration of annual extreme water conditions	IHA Group 4: Frequency and duration of high- and low flow pulses	Extreme environmental flow conditions (EFC) parameters
October flow	Annual minimums of 1-day means	Low pulse count	Extreme low peak
November flow	Annual maximums of 1-day means	Low pulse duration	Extreme low duration
December flow	Annual minimums of 3-day means	High pulse count	Extreme low timing
January flow	Annual maximums of 3-day means	High pulse duration	Extreme low frequency
February flow	Annual minimums of 7-day means		High flow peak
March flow	Annual maximums of 7-day means		High flow duration
April flow	Annual minimums of 30-day means		High flow timing
May flow	Annual maximums of 30-day means		High flow frequency
June flow	Annual minimums of 90-day means		High flow rise rate
July flow	Annual maximums of 90-day means		High flow fall rate
August flow	(taken from moving averages and always		Small flood peak
September flow	calculated as means)		Small flood duration
(median value for each calendar			Small flood timing
month)			Small flood rise rate
			Small flood fall rate
			Large flood peak
			Large flood duration
			Large flood timing
			Large flood rise rate
			Large flood fall rate

flows simulated using downscaled climate output. The RVA used the flows simulated using historical climate data as a reference for defining the extent to which "natural flow regimes" differed from flows simulated using dGCM output. For the RVA, the streamflow data were split into 3 categories: (1) data above 66th percentile as high RVA (analysis of high flows), (2) data between 33rd and 66th percentile as medium RVA, and (3) data below 33rd percentile as low RVA (analysis of low flows). It was hypothesised that the high RVA would capture the increase or decrease of high values (including extreme high flow values: floods) in streamflow simulated using dGCM output. Likewise, the low RVA was hypothesised to be able to capture the increase or decrease of low values (including extreme low flow values: droughts) in streamflow simulated using dGCM output. Hydrologic Alteration factors, quantifying the degree of alteration for the 33 IHA flow parameters (Table 2) were calculated.

3. Results

The following sections detail the performance of the dGCMs in capturing historical rainfall, the performance of the ACRU model in simulating streamflow, and how the simulated streamflow (simulated using dGCM output) captures the spatial variability and magnitudes of high and low flows compared to streamflow simulated using historical climate data.

3.1. Evaluation of the downscaled rainfall

Kusangaya et al. (2016) in a study aimed at evaluating how downscaled climate output represented the underlying historical precipitation characteristics beyond the means and variances showed that using the means and variances, most dGCMs could satisfactorily represent historical rainfall (e.g. 7/10 dGCMs were within ± 10% of historical rainfall mean), whilst few (3/10 dGCMs) did not capture the mean and variability of rainfall well (Table 3). Additionally, beyond the means and variances, the performance of the downscaled rainfall showed that high rainfall events were well captured whilst raindays and low rainfall events were poorly captured. Furthermore, raindays and low rainfall events were poorly captured in summer (December–February) as compared to the low rainfall winter months (June–August).

3.1.1. Evaluation of extreme rainfall

Evaluation of extreme rainfall was carried out using the number of raindays with rainfall exceeding 50 mm per day to the number of raindays with rainfall exceeding 200 mm per day. Results (Table 4) indicated that all the GCMs captured the extreme raindays very well with correlation coefficient ranging from 0.923 to 0.998.

3.2. Evaluation of the performance of the ARCU hydrological model

Warburton et al. (2010) showed that, overall, the ACRU model performed well on each of the four WMUs which had flow measuring stations, hence the ACRU model can confidently to simulate streamflows of the Mgeni catchment. For example, for the Mpendle WMU, the total flows are adequately simulated with the percentage difference between the observed and simulated standard deviation were found to be less than 15%, the R^2 of daily values was 0.836 and the Nash-Sutcliffe E_f was 0.802. Therefore, simulation of streamflow in the Mpendle WMU was considered highly acceptable. The Lions River WMU on the other hand, similarly produced acceptable results with an R^2 of 0.882. For the Karkloof WMU, the Nash-Sutcliffe E_f of 0.655 and the other statistics were also considered acceptable (Table 5). The results of the confirmation study for the Henley WMU were considered reasonable as all statistics, except for the percentage difference between the standard deviations were acceptable, and comparison of daily simulated and observed streamflows indicated that the variability of streamflow was adequately simulated.

3.3. Annual and monthly variability of streamflows

Streamflow simulated using historical climate data had a greater range of annual flow variability (0.002–0.016 m^3/s) when compared with streamflow simulated using dGCM output, with variability ranging from 0.001 to 0.010 m^3/s (Fig. 4). The inability of streamflow simulated using dGCM output to capture the variability in annual data series implied that streamflow simulated using dGCMs is not capable of replicating extreme river dynamics (high and low flows) observed in streamflow simulated using historical climate data. On a monthly basis, it was also established that, streamflow simulated using historical climate data was largely underestimated by as much as 50% in the high rainfall months in summer (December–March). This

Table 3
Percentage difference in mean values between downscaled GCM rainfall and historical rainfall for the period 1961–2000, highlighting (in bold) all cases were the rainfall was within the ±5% of historical rainfall mean for each of the rainfall stations.

Rainfall station	cc1	cn1	cs1	e11	e12	g11	g12	gi1	ip1	mr1
0238662_A	−14.33	**−0.52**	**0.51**	−6.03	−8.93	**4.21**	9.97	25.71	**2.16**	−5.46
0239002_W	−13.56	**0.12**	**0.51**	−5.65	−8.47	**4.33**	10.49	25.97	**2.88**	−5.81
0269111_A	−9.41	17.22	8.54	**3.67**	−5.58	7.83	25.26	32.47	12.08	−6.78
0269295_A	−12.72	15.88	6.84	**0.61**	−8.07	5.98	21.82	30.56	10.11	−9.54
0239184_A	−11.79	8.53	6.39	**−1.97**	−7.43	6.48	21.52	28.43	**4.97**	−6.76
0239482_A	−5.40	18.19	17.59	7.91	**−4.05**	18.50	23.96	39.64	25.00	**−1.19**
0239518_W	−15.08	7.70	−10.16	−6.40	−10.79	−7.63	**0.41**	26.26	**4.02**	−9.84
0239700_A	−16.43	7.66	−11.24	−7.45	−11.18	−8.00	**−0.83**	25.26	**2.90**	−9.90
0269532_A	**−0.28**	19.73	13.59	9.31	**0.05**	13.85	19.79	31.49	28.55	**4.30**
0270021_W	−15.27	**2.31**	−8.42	−7.34	−12.08	−5.43	**−1.08**	6.80	8.76	−10.44
0270119_W	−8.77	8.20	**1.42**	**1.50**	−7.81	**2.12**	8.66	20.60	17.79	−5.47
0240073_W	−14.69	8.72	−9.67	−5.63	−10.17	−7.29	**0.82**	26.86	**4.40**	−9.40
0270329_S	−13.56	**0.12**	**0.51**	−5.65	−8.47	**4.33**	10.49	25.97	**2.88**	−5.81
0240404_W	−9.19	12.05	−5.89	**−3.76**	−7.75	−7.44	7.27	26.30	**1.80**	−12.19
0240738_W	−4.42	16.30	**−2.93**	**4.75**	**−4.97**	−5.22	10.84	27.76	10.94	**0.10**
Between (±5%)	**2**	**4**	**5**	**6**	**3**	**4**	**4**	**0**	**8**	**3**
Between (±10%)	6	**9**	**11**	**15**	**11**	**13**	7	1	**9**	**13**

Between (±5%): dGCM rainfall lying between (±5%) of historical rainfall.

Table 4
Correlation (Pearson's R) between GCM and observed of raindays with rainfall from 50 mm per day to 200 mm per day (considered as extreme rainfall).

Catchment	Rainfall station	GCMs									
		cc1	cn1	cs1	e11	e12	g11	g12	gi1	ip1	mr1
Mpendle	0239002W_upd	0.992	0.993	0.989	0.988	0.994	0.992	0.996	0.995	0.980	0.997
Lions River	0269111A	0.953	0.948	0.924	0.953	0.974	0.923	0.931	0.933	0.967	0.986
Karkloof	0269532A	0.972	0.977	0.969	0.974	0.980	0.957	0.958	0.959	0.976	0.968
Nagle	0270119W	0.995	0.971	0.995	0.992	0.996	0.983	0.983	0.988	0.995	0.995
Pietermaritzburg	0239700A	0.989	0.986	0.994	0.995	0.988	0.989	0.994	0.978	0.992	0.983
Table Mountain	0240073W	0.980	0.993	0.994	0.995	0.991	0.988	0.995	0.990	0.989	0.992
Midmar	0239184A	0.993	0.996	0.994	0.995	0.995	0.982	0.982	0.985	0.998	0.998
New Hanover	0270021W	0.990	0.986	0.980	0.995	0.986	0.987	0.993	0.995	0.998	0.988
Inanda	0240404W	0.993	0.980	0.995	0.992	0.991	0.993	0.994	0.996	0.990	0.990
Mqeku	0270329S	0.992	0.993	0.989	0.988	0.994	0.992	0.996	0.995	0.980	0.997
Durban	0,240,738W	0.996	0.996	0.996	0.997	0.995	0.996	0.993	0.998	0.990	0.997

Table 5
Statistics showing the performance of the *ACRU* model in the Mgeni Catchment: Comparison of daily historical and simulated values for the period 1960–2000. (). Source: Warburton et al., 2010

Flow metrics	WMU			
	Mpendle	Lions River	Karkloof	Henley
Total observed flows (mm)	3444.068	2507.196	3456.985	2635.724
Total simulated flows (mm)	3171.486	2257.643	3005.969	2533.988
Ave. error in flow (mm/day)	−0.063	−0.058	−0.105	−0.024
Mean observed flows (mm/day)	0.796	0.582	0.803	0.629
Mean simulated flows (mm/day)	0.733	0.524	0.698	0.605
% Difference between means	7.91%	9.95%	13.05%	3.86%
Std. Deviation of observed flows (mm)	1.823	1.734	1.228	1.246
Std. Deviation of simulated flows (mm)	2.011	1.947	1.305	1.541
% Difference between Std. Deviations	−10.34%	−12.31%	−6.26%	−23.67%
Correlation Coefficient: Pearson's R	0.915	0.939	0.844	0.886
Regression Coefficient (slope)	1.009	1.055	0.897	1.095
Regression Intercept	−0.07	−0.09	−0.022	−0.084
Coefficient of Determination: R2	0.836	0.882	0.713	0.785
Nash-Sutcliffe Efficiency Index (Ef)	0.802	0.847	0.655	0.654

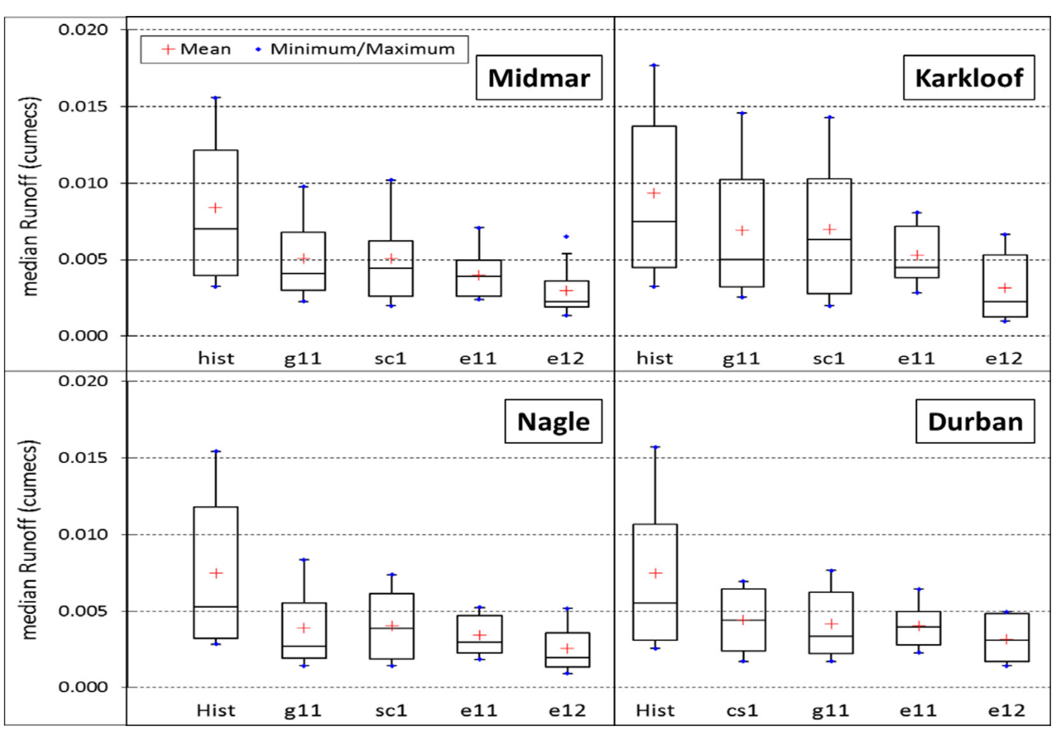

Fig. 4. Annual median flow variability for Midmar, Karkloof, Nagle and Durban Catchments (Hist = Historical, e11 = MIUB_ECHO_G, e12 = MPI_ECHAM5, cs1 = CSIRO_MK3_5, g11 = GFDL_CM2_0, mr1 = MRI_CGCM2_3_2A).

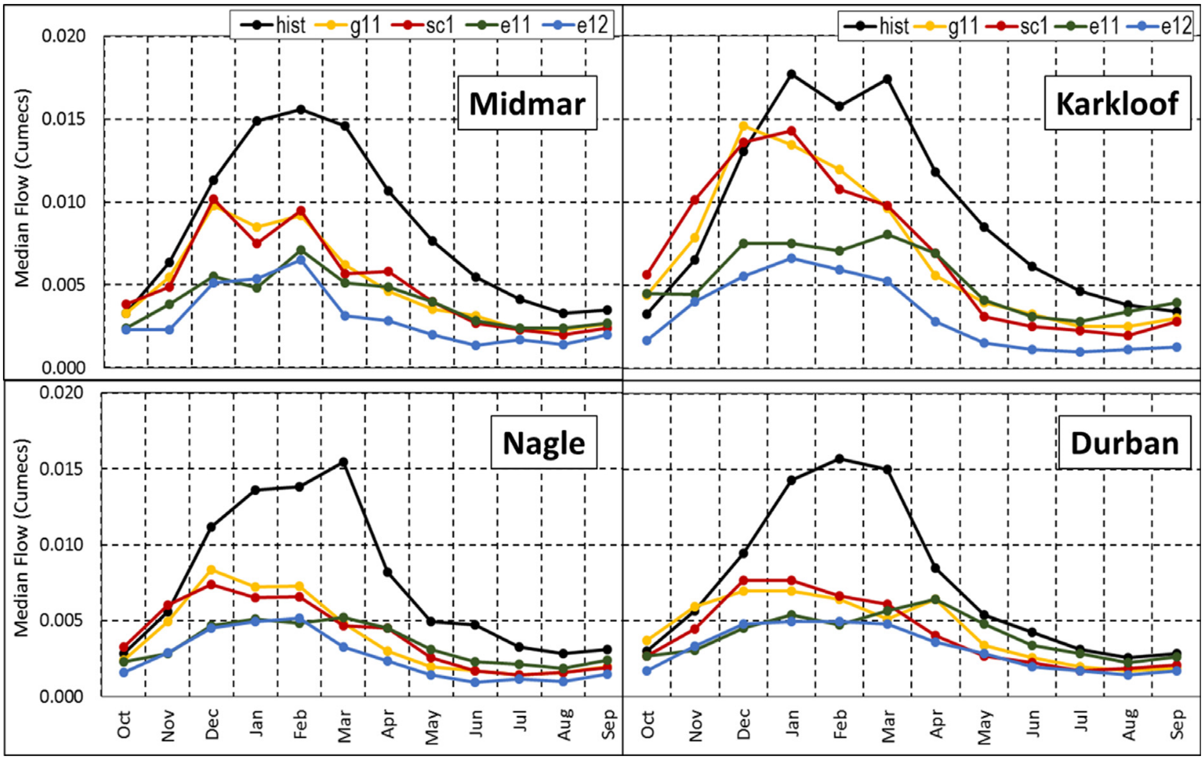

Fig. 5. Monthly median flows for Midmar, Karkloof, Nagle and Durban Catchments from IHA group 1 Parameters.

could largely be attributed to the failure of the dGCM simulated streamflow in capturing local storms and related streamflow peaks which normally occur during the summer season. These summer months were also characterised by a greater range in variability in all the study catchments. For the winter months (May–July), streamflow simulated using historical climate data was underestimated. Fig. 5 shows the monthly median flow variability for Midmar, Karkloof, Nagle and Durban Catchments.

Results from the deviation factor and the corresponding significant count analysis (Table 6) indicate that for all catchments (Midmar, Karkloof, Nagle and Durban), the deviation of the streamflow simulated using dGCMs from the streamflow simulated using the historical data were highly significant in most of the metrics used. This implied that there were significant differences between the streamflow simulated using historical climate data and streamflow simulated using dGCM output.

3.4. Magnitude and duration of annual extreme flows

A suite of indices depicting magnitude and duration of annual extreme streamflow conditions (low and high flows indices) were calculated. These included the 1-, 3-, 7-, 30-, and 90-day minimums and maximums taken from moving averages calculated (as means) for every possible period that is completely within the water year:1 October to 30 September (Nature-Conservancy, 2009). Results indicated that for all WMUs, the magnitude of low flows increased with increasing frequency of low flows (1-, 3-, 7-, 30-, 90 day minimum) (Fig. 6). Even though the simulated streamflow from dGCMs failed to correctly capture the magnitude (underestimation), the increasing pattern (from 0.001 for 1 day minimum to 0.004 for the 90 day minimum) was well captured in all the WMUs.

The magnitude of high flows decreases with increasing frequency of high flows (1-, 3-, 7-, 30-, and 90-day maximums) (Fig. 7). For most of the WMUs, high flows were overestimated, especially in the catchment areas of uMngeni Catchment receiving moderate rainfall (between 700 and 900 mm). On the other hand, for the high rainfall Karkloof WMU, streamflow simulated using dGCMs climate output underestimated streamflow simulated using historical climate data. Again as in the low flow analysis, the decreasing pattern with increasing frequency: 1-, 3-, 7-, 30-, and 90-day maximums, in high flow magnitude was well captured in all WMUs.

3.5. Hydrological variability of high and low flows

As stated above for the RVA, the streamflow data were split into three categories: (a) data above 66th percentile as High RVA (analysis of high flows), (b) data between 33rd and 66th percentile as medium RVA, and (c) data below 33rd percentile as low RVA (analysis of low flows). It was hypothesised that the high RVA would capture the increase or decrease of high values (including extreme high flows: floods) in streamflow simulated using dGCM output. Likewise, the low RVA was hypothesised to be able to capture the increase or decrease of low flows (including extreme low values: droughts) in streamflow simulated using dGCM output. Overall, results from the four selected WMUs showed that in the high and middle RVA ranges, the majority of IHA parameters considered in this study were characterised by negative HA values. A negative value means that the frequency of values in the high and middle RVA ranges was lower for the streamflow simulated using the historical climate data as compared to streamflow simulated using the dGCM output. This implied that streamflow simulated using dGCM output did not capture all the high and extreme high flow values as captured in the streamflow simulated using historical climate data.

Table 6
An example of deviation factors and significant count of Durban sub-catchment in lower uMngeni Catchment [all significant deviation (SC < 0.05) are shown in bold].

DURBAN	Deviation factor (DF)				Significance count (SC)			
	g11	cs1	e11	e12	g11	cs1	e11	E12
Parameter group #2								
1-day minimum	0.36	0.27	0.27	0.64	**0.00**	**0.00**	**0.00**	**0.05**
3-day minimum	0.37	0.31	0.29	0.54	**0.00**	**0.02**	**0.00**	**0.04**
7-day minimum	0.34	0.31	0.22	0.52	**0.00**	**0.00**	**0.00**	**0.03**
30-day minimum	0.31	0.29	0.29	0.45	**0.01**	**0.01**	**0.05**	**0.00**
90-day minimum	0.21	0.25	0.01	0.34	**0.13**	**0.08**	0.87	**0.04**
1-day maximum	0.19	0.07	0.18	0.28	**0.02**	0.63	**0.08**	**0.07**
3-day maximum	0.02	0.10	0.06	0.17	0.87	**0.40**	0.69	**0.29**
7-day maximum	0.09	0.14	0.02	0.04	**0.49**	**0.34**	0.92	0.66
30-day maximum	0.06	0.14	0.05	0.07	0.69	**0.19**	0.81	0.58
90-day maximum	0.10	0.21	0.16	0.25	**0.13**	**0.01**	**0.16**	**0.01**
Parameter group #4								
Low pulse count	1.63	1.19	1.56	1.75	**0.00**	**0.00**	**0.00**	**0.00**
Low pulse duration	0.33	0.33	0.33	0.67	**0.01**	**0.01**	**0.02**	**0.00**
High pulse count	0.30	0.40	0.20	0.20	**0.00**	**0.00**	**0.00**	**0.01**
High pulse duration	0.25	0.31	0.38	0.44	**0.07**	**0.05**	**0.01**	**0.00**
EFC parameters								
Extreme low peak	0.08	0.00	0.00	0.17	**0.20**	**0.13**	**0.05**	**0.02**
Extreme low duration	0.13	0.00	0.19	0.00	**0.46**	**0.34**	**0.35**	**0.56**
Extreme low freq.	2.56	2.22	2.56	4.33	**0.00**	**0.00**	**0.00**	**0.00**
High flow duration	0.50	0.50	0.50	0.50	**0.01**	**0.00**	**0.00**	**0.01**
High flow frequency	0.53	0.53	0.41	0.20	**0.00**	**0.00**	**0.00**	**0.00**
Small Flood duration	0.38	0.38	0.34	0.47	**0.01**	**0.08**	**0.04**	**0.02**
Small Flood rise rate	0.46	1.12	0.62	1.94	**0.14**	**0.01**	**0.07**	**0.00**
Small Flood fall rate	0.40	0.18	0.42	0.75	**0.00**	**0.33**	**0.01**	**0.00**
Large flood peak	0.01	0.05	0.43	0.12	0.82	**0.39**	**0.11**	0.58
Large flood duration	0.71	0.63	0.61	0.65	**0.35**	**0.36**	**0.18**	**0.47**
Large flood timing	0.83	0.83	0.15	0.03	**0.68**	**0.20**	**0.74**	**0.93**
Large flood rise rate	7.02	0.08	3.61	2.93	**0.08**	0.80	**0.07**	**0.14**
Large flood fall rate	1.58	1.02	1.95	1.72	**0.09**	**0.13**	**0.01**	**0.06**

Deviation Factor (DF): Deviation of the dGCM output simulations from the Historical runoff data defined as (dGCM output value) – (Historical value)|/(Historical value).
Significance Count (SC): For the deviation values for which the median deviation values from the dGCM were greater than for the simulation from historical climate data. A low significance count (minimum value is 0) means that the difference between the pre- and post-impact periods is highly significant, and a high significance count (maximum value is 1) means that there is little difference between the pre- and post-impact periods. The significance count can be interpreted similarly to a p-value in parametric statistics (Nature-Conservancy, 2009).

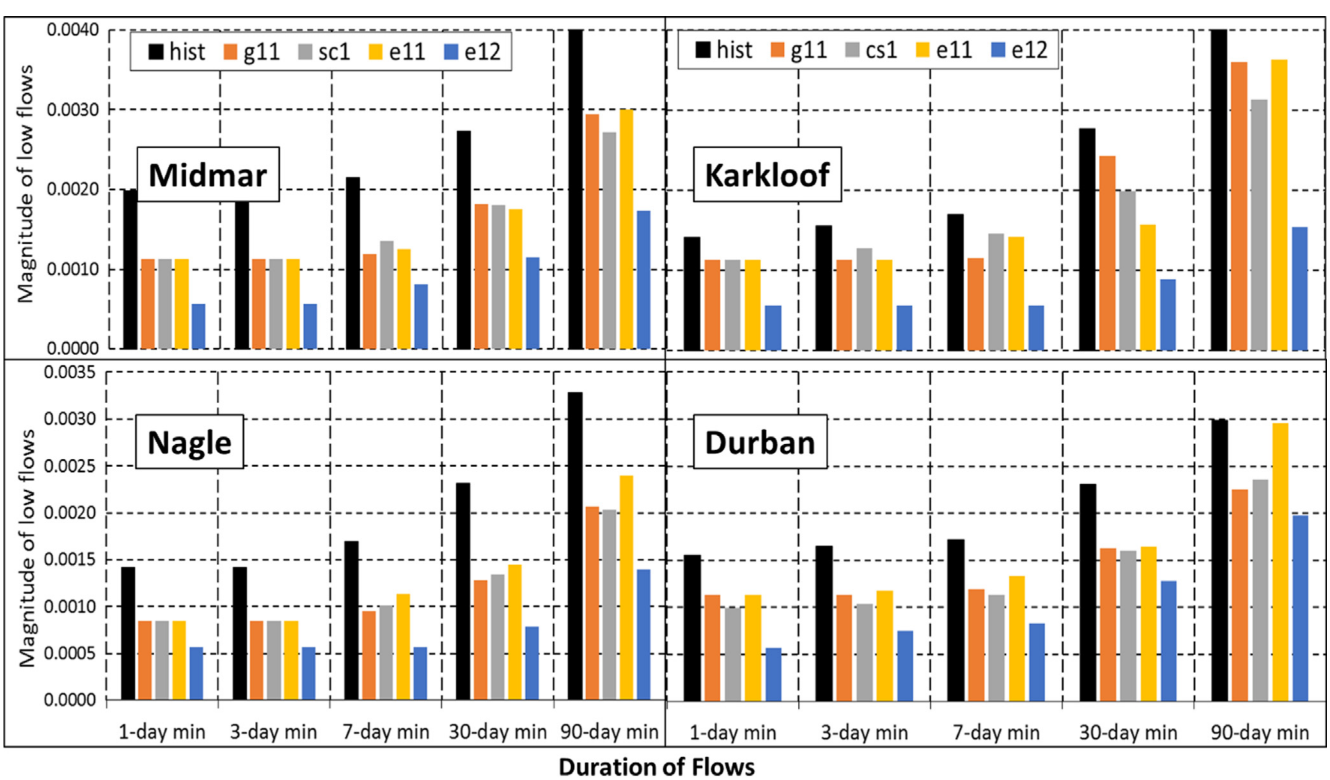

Fig. 6. Magnitude of low flows with increasing duration (1-, 3-, 7-, 30-, and 90-day minimums) of low flow events for the four WMUs: Midmar, Karkloof, Nagle and Durban.

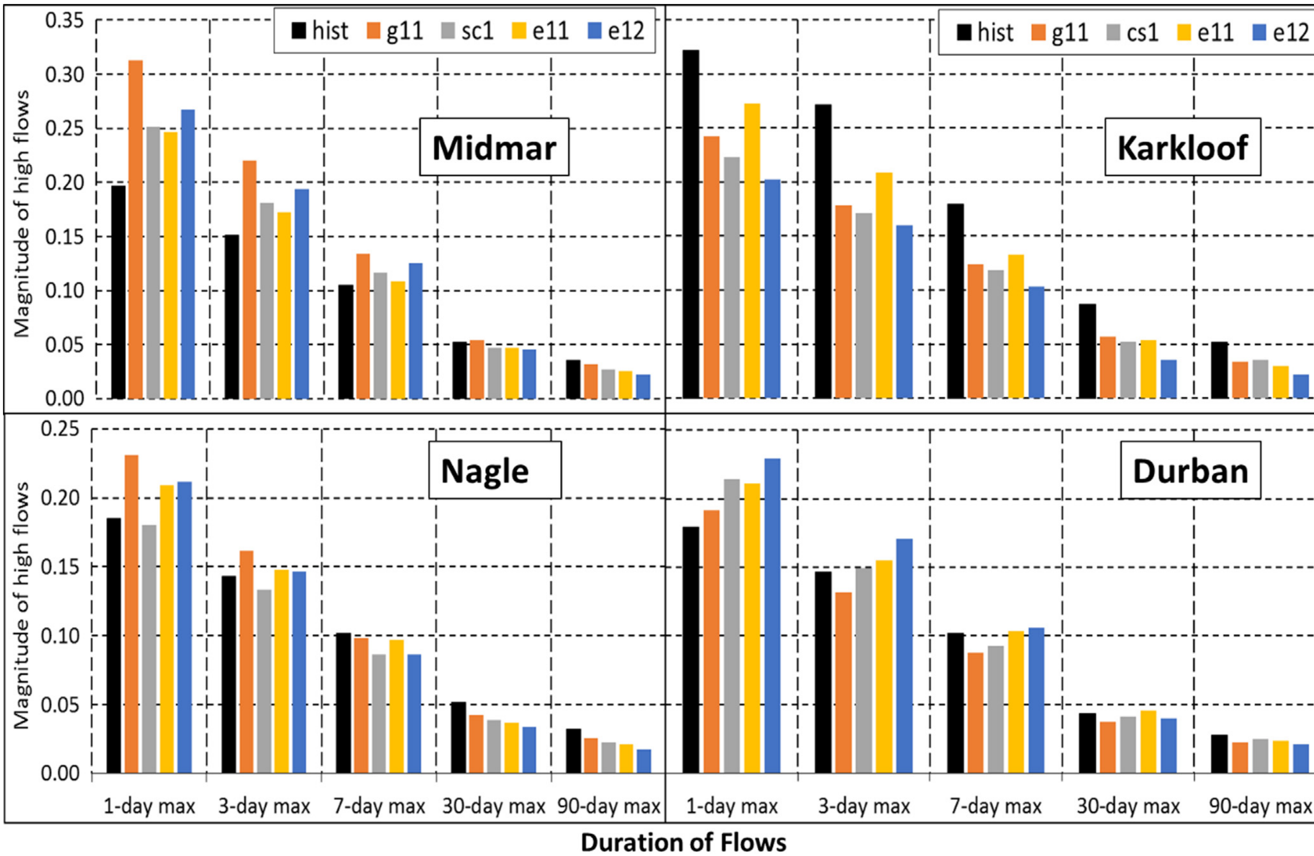

Fig. 7. Magnitude of high flows with increasing duration (1-, 3-, 7-, 30-, and 90-day maximums) of high flow events for the four WMUs: Midmar, Karkloof, Nagle and Durban.

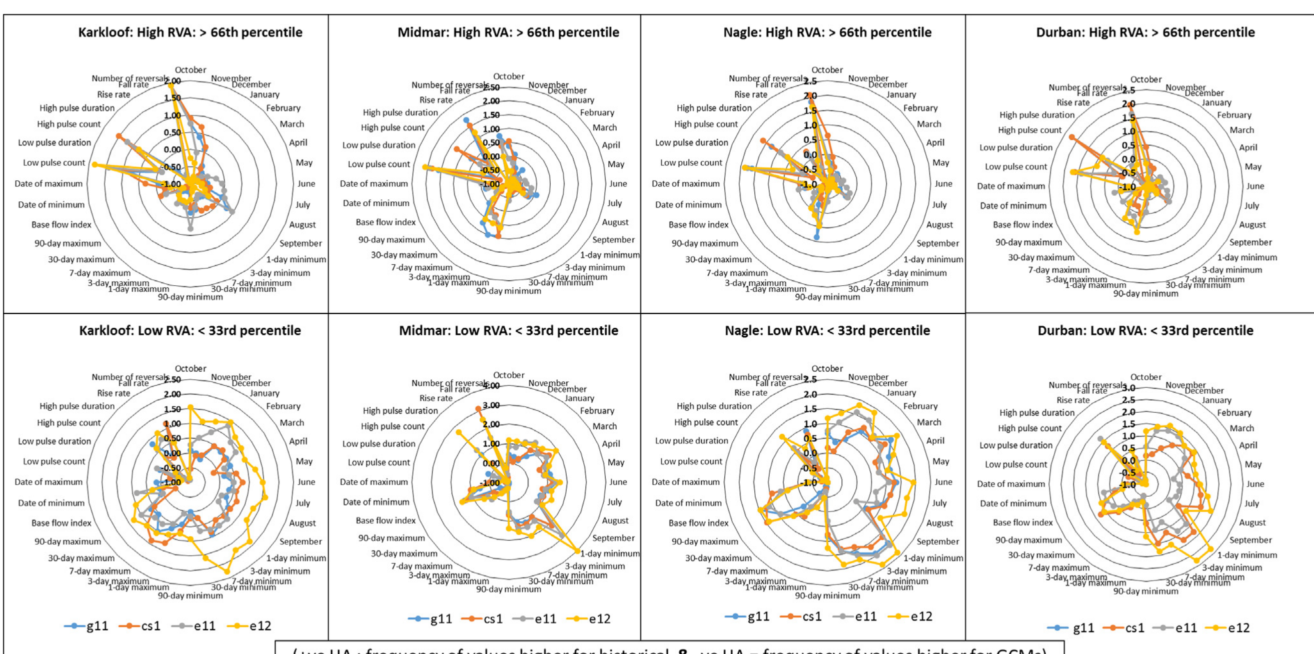

Fig. 8. Range of variability analysis results for the uMngeni Catchment showing hydrological alteration for Karkloof and Midmar WMUs (in the upper catchment area and receives high rainfall >900 mm), Nagle and Durban WMUs (in the lower catchment area and receives medium rainfall between 850–960 mm).

Similarly, all IHA parameters were characterised by negative HA values for the low RVA. This implied that the frequency of values in the low IHA category was lower for the streamflow simulated using the historical climate data as compared to streamflow simulated using the dGCM output. This meant that streamflow simulated using dGCM output was capturing less episodes of low flows as compared to the low flows simulated using historical climate data. Fig. 8 shows a summary of

hydrological indicators for all the parameters analysed (for high and low flow assessments) using the IHA range of variability approach.

Generally Fig. 8 shows that high RVA (for high flow analysis), the HA factor for low pulse count, high pulse count, rise rate and fall rate is more than one for Karklof, Midmar, Nagle and Durban WMUs. On the other hand the 1, 3 and 7 day minimum as well as the monthly median flows were also characterised by a HA greater than one for the low RVA (for low flow analysis). As stated before, a positive HA value implies that the frequency of values in the category (high, or low RVA) has increased from the streamflow simulated using the historical climate data (pre-impact) to the streamflow simulated using the dGCM output (post impact).

3.6. Extreme high and low flow parameters

Using the range of variability analysis of environmental flow conditions, parameters examining extreme high/low flows were considered. Of the 20, the following 10 EFC parameters were found to be significantly (significant count less than 50%) different from the streamflow simulated using historical climate data from at least one dGCM: extreme low peak, extreme low frequency, high flow peak, high flow duration, high flow frequency, high flow rise rate, high flow fall rate, small flood duration, small flood rise rate, small flood fall rate (Fig. 9). As such, the remaining 10 parameters (extreme low duration, extreme low timing, high flow timing, small flood peak, small flood timing, large flood peak, large flood duration, large flood timing, large flood rise rate, and large flood fall rate) showed that there was no significant difference in these parameters between streamflow simulated using historical climate data and streamflow simulated using dGCM output (Fig. 9).

Most of the streamflow simulated using climate data from dGCMs successfully captured the large flood peak (between 0.4 and 1.0 m^3/s) (Fig. 10A), except for dGCM e11, which was characterised by variability ranging between 0.5 and 1.3 m^3/s. Large flood duration, however, was underestimated by streamflow simulated using dGCM output (Fig. 10B) by as much as 25–30 days. Extreme low flow frequency (Fig. 10C) was overestimated in streamflow simulated using historical climate data than streamflow simulated using dGCM output. Extreme low flow duration (Fig. 10D) on the other hand was comparable (all between 2 and 4 days) between simulated streamflow from downscaled dGCMs output and historical climate data.

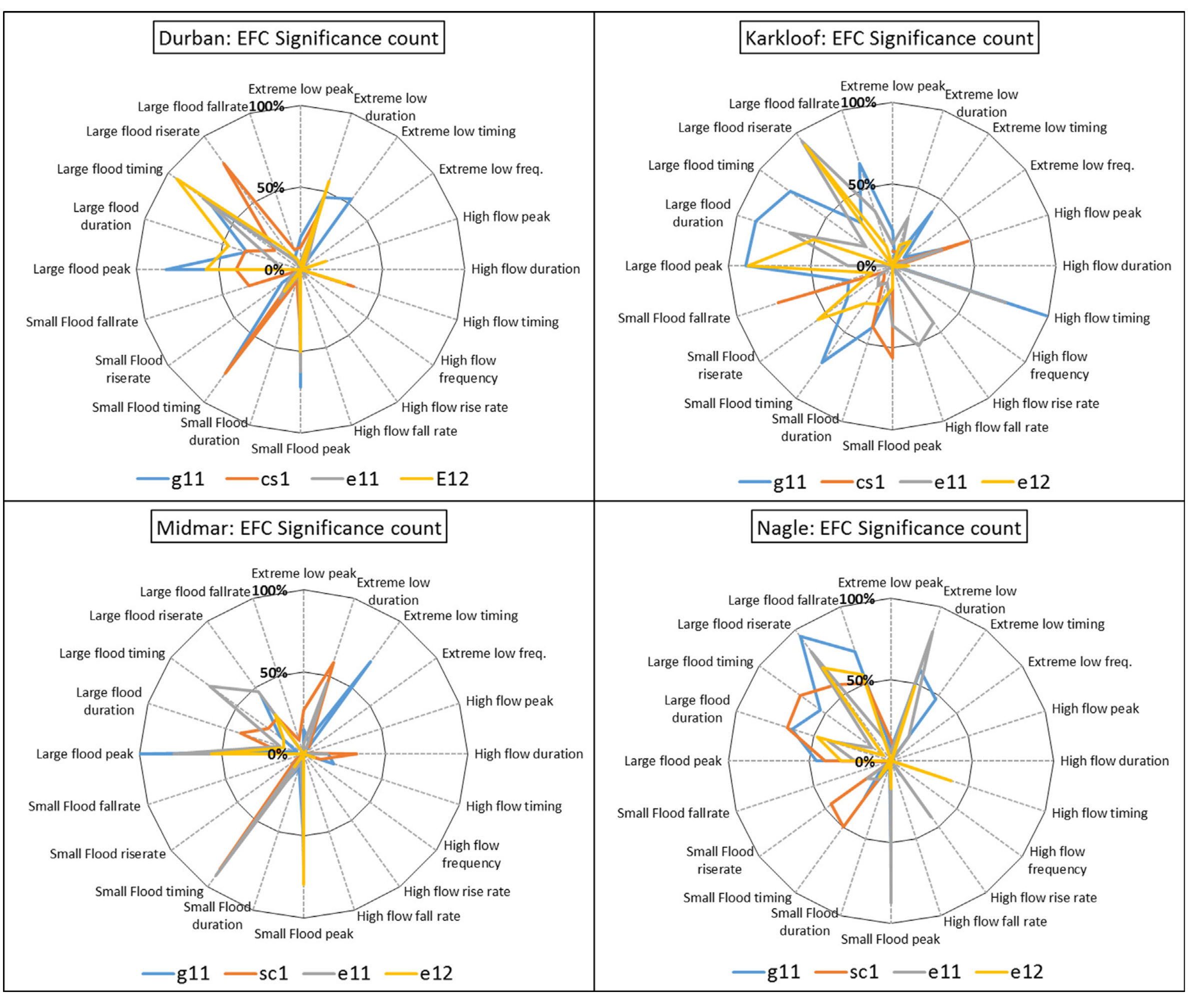

Fig. 9. Significance of deviation of streamflow simulated using dGCM output from streamflow simulated using historical climate data, expressed as a percentage where a low significance count (<50%) meant that the difference between the streamflow simulated using historical climate data and streamflow simulated using dGCM output was highly significant.

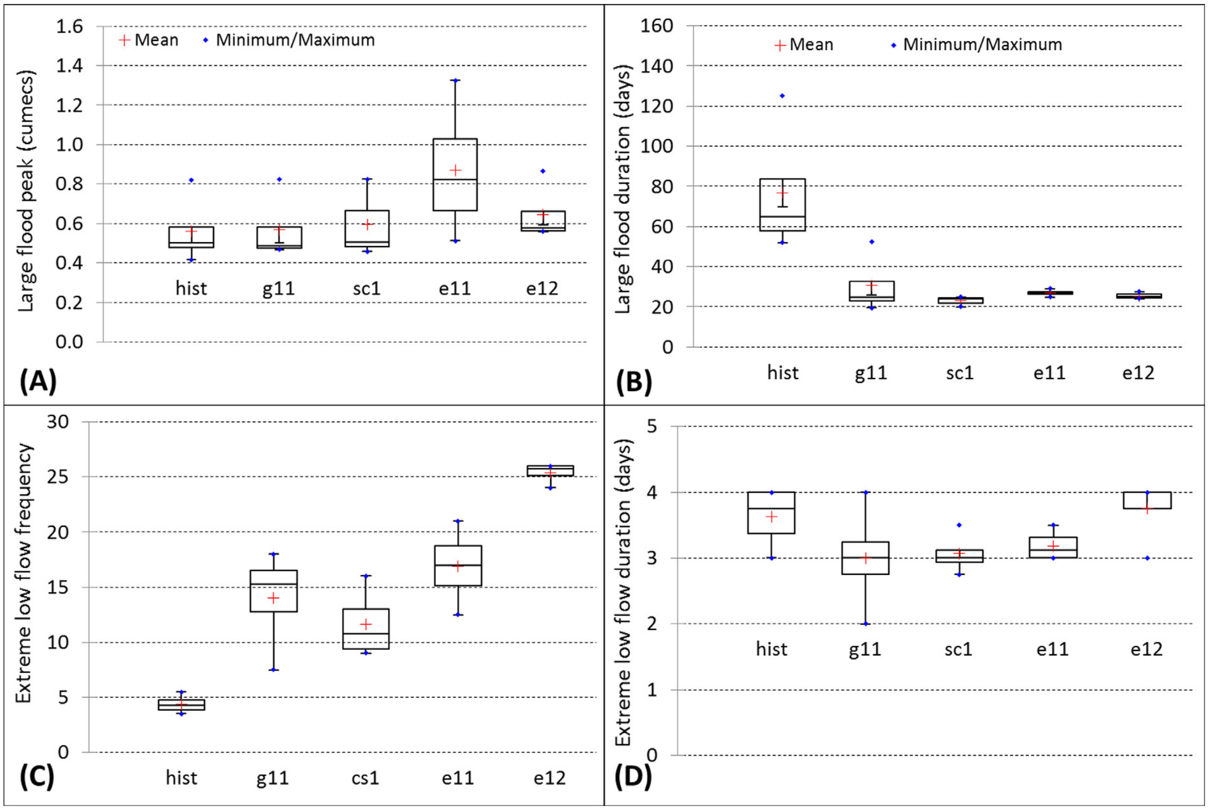

Fig. 10. Example of extreme low and high flows frequency and duration and peak flow variation between streamflow simulated using historical climate data versus streamflow simulated using dGCM output.

4. Discussion and conclusions

This study tested how simulated streamflow using dGCM output captures river dynamics (high and low flows) in the uMngeni Catchment of South Africa. Results of this study indicate that in moderately high to high rainfall catchments, streamflow simulated using historical climate data were underestimated compared to streamflow simulated using dGCMs output. This was despite the fact that all the chosen dGCMs had captured overall rainfall mean and variability reasonably well (e.g. were within ±10% of historical rainfall mean). Such a result implies that dGCMs introduce greater uncertainty in high rainfall areas, possibly owing to the failure of the dGCMs to capture adequately other rainfall characteristics such as (a) total rainfall quantity, (b) the interval between rainfall events, or (c) individual event size (d) rainfall duration, and (e) rainfall intensity. Thus, when used to simulate streamflow, it resulted in the peak, duration and frequency of streamflow events not being adequately captured, especially in high rainfall areas. The inability of dGCMs to correctly represent rainfall characteristics is widely reported in literature (see, e.g. Nemeth, 2010; Prudhomme et al., 2010; Tramblay et al., 2012; Willems et al., 2012; Ntegeka et al., 2014). Recently, Teng et al. (2015) showed that raw regional climate model (RCM) precipitation exhibited negative errors in annual and seasonal means, with the median errors in raw RCM annual means. Generally, it has been established that input data uncertainty, in particular uncertainty associated with rainfall data input, significantly affects the total simulation uncertainty (Andréassian et al., 2001; Pappenberger et al., 2005). On the other hand, Schulze (1995) established that output simulated by the *ACRU* hydrological model is most sensitive to input rainfall. Consequently, the uncertainties in river dynamics (high and low flows) described in this study were hypothesised to be largely due to the uncertainties in the precipitation outputs from dGCMs rather than uncertainties in the ACRU model itself. The results obtained in this study for uMngeni Catchment thus concur with other studies elsewhere as cited above.

During the summer rainfall months, simulated streamflow was characterised by greater variability and during the low rainfall winter months, simulated streamflow was characterised by less variability. This result suggests that for summer rainfall characterisation, dGCMs fail to capture the extremes of rainfall (i.e. rainfall peaks). This error was carried on and even propagated to the simulated streamflow as demonstrated by poor detection of simulated streamflow extremes. This is understandable, since rainfall is the major driver of the hydrological cycle, thus largely determining characteristics of simulated streamflow. The above conclusions have been collaborated in literature. For example (Chiew et al., 2009; Teng et al., 2012; Teng et al., 2015) have reported the so called "drizzle effect" whereby downscaled climate output simulates too many low-intensity precipitation events and too few high-intensity precipitation events. These results are also in agreement with recent findings from Coppola et al. (2014), who, using eight scenario runs from two regional climate models, established that, the uncertainty associated with the winter streamflow change was larger compared to that in the fall. This study was carried out in Italy, for the Po River which is characterised by two annual discharge maxima, one in spring (because of snow melting in the Alps) and one in the fall (due to rainfall in the area at this time of the year). The uMngeni Catchment, however, only experiences one annual discharge maximum as it receives most rainfall during the summer months (December–March).

When streamflow data were split into percentiles, median flows for all the streamflow data above 67th percentile and data between 33rd and 66th percentile was largely characterised by negative HA

values, implying that the frequency of values in the high and middle RVA ranges was lower for the streamflow simulated using the historical climate data. This implied that streamflow simulated using dGCM output did not capture the high and extreme high flows that were captured in the streamflow simulated using historical climate data. It is thus concluded that dGCMs do not adequately capture extreme high values characteristic of for example cyclonic/heavy storm events, further translating to extreme high flows not being well represented in hydrological modelling. These results are in agreement with results by Mandal et al. (2016), who found that a large amount of uncertainty was evident in summer high precipitation months (June, July and August) as compared to the low rainfall periods.

On the other hand, for the data below the 33rd percentile, positive HA meant that the frequency of values in the low HA category was higher for the streamflow simulated using the historical climate data, as compared to streamflow simulated using the dGCM output. This implies that simulated streamflow using dGCM output captured more low flows and more extreme low flows than what actually was occurring as in the streamflow simulated using historical climate data – the so called "drizzle effect" reported also by Teng et al. (2012). Consequently, simulated dGCM streamflow would show more drying/droughts than actually exists. Thus, as reported also in (Nemeth, 2010; Prudhomme et al., 2010; Willems et al., 2012; Ntegeka et al., 2014) downscaled climate products are unable to capture the spatial variability and magnitudes of extreme hydrological events which are often of particular concern in hydrology.

Although the method of IHA is effective as it uses a range of indices to analyse various aspect of flow regimes, it utilises an extensive set of indices, which in most cases are correlated (Olden and Poff, 2003; Gao et al., 2009), hence this results not only in a level of numerical redundancy in data processing, but also in considerable information redundancy. Yang et al. (2008) identified a small subset of hydrological indicators that were the most representative of ecological flow regimes. Oueslati et al. (2010) used principal components analysis to reduce 40 hydrological indices to identify subsets of hydrological indices that describe the major sources of variations while minimizing redundancy, and showed that the number of statistically significant principal components varied from three to four. For this study, a total of 40 of the 67 IHA indices, 26 of the 33 HA (Group 1, 2, and 4) and 20 of the 34 EFC were used. This resulted not only in a level of numerical redundancy in data processing, but also in considerable information redundancy. However, the "ideal" approach as reviewed from literature is to use a suite of indices in the analysis of both high and low flows (see, e.g., Khomsi et al., 2016). From the above discussion this study concludes that developing a small number of statistics that capture key components of hydrologically relevant flow variation will: (1) contribute to a general approach for characterizing flow alteration, (2) minimize statistical redundancy and computational effort in future analyses.

The overall conclusion of this study is that dGCM output were characterised by higher uncertainties, especially in capturing extreme hydrological parameters such as extreme high and low flows. Streamflow simulation using dGCM output does not capture extreme hydrological events, which are often of particular concern in design hydrology, especially under conditions of increasing frequency of extreme hydrological events (floods and droughts) and the subsequent changes in river dynamics (high and low flows). Consequently, streamflow simulated using dGCMs should be used with caution for hydrological applications, particularly when considering extreme flows. For example, Ruelland et al. (2015) cautioned that the use of streamflow simulated from GCMs must be limited to the analysis of mean shifts in the future and that it cannot be designed for analysing the impacts of potentially more intense drought or flood events. It is therefore recommended that downscaling techniques be improved in order to generate climate data that are relevant for hydrological assessments. Be that as it may, the availability of downscaled climatic output provide the potential of exploring climate model uncertainties in different hydro-climatic regions at local scales where forcing data is often less accessible but more accurate at finer spatial scales and with adequate spatial detail.

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